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Introduction

Blended learning and other types of technology-enhanced education offer unique opportunities to investigate traditional, educational research questions from new perspectives: '*The advance of technology-enhanced learning environments is opening up new opportunities for reconstructing and analysing students' learning behavior.*' (Schumacher and Ifenthaler, 2018, p. 397). The use of multi-modal data, which is characterised by two or more distinct types of data, offers new insights into long-standing academic debates that have been addressed in the past with empirical studies based on survey data only. The availability of trace data derived from the use of technology-enhanced learning, trace data of both process and product types (Azevedo *et al*., 2013), is a crucial aspect in this progress made in analysing learning behaviours. Learning analytics (LA) methods, that use '*dynamic information about learners and learning environments, assessing, eliciting and analysing it, for real-time modelling, prediction and optimisation of learning processes, learning environments and educational decision-making*' (Ifenthaler, 2015), have boosted the use of trace data in research applications. However, most 'classical' LA research suffers from the same shortcomings as classical educational research: they often use only one type of data, this time trace data, and thus focus on one single perspective.

Recently, several multi-modal studies have started to integrate different types of learning analytics data as well as exploring learning from an intertemporal perspectives. Examples of studies applying multi-modal data are Duffy and Azevedo (2015), analysing goal setting survey data in combination with trace data, or Sergis *et al.* (2018), analysing self-determination based motivational survey data in combination with trace data. A related approach is that of Dispositional Learning Analytics (DLA, Buckingham Shum and Crick, 2012), that proposes an infrastructure that combines learning data (generated in learning activities through technology-enhanced systems) with a broad range of learner data: student dispositions, values, and attitudes measured through self-report surveys. Learning dispositions represent individual difference characteristics that impact all learning processes and include affective, behavioural and cognitive facets (Rienties *et al*., 2017). Students' preferred learning approaches are examples of such dispositions of both cognitive and behavioural type. In a series of studies (Nguyen *et al*., 2016; Tempelaar *et al*., 2015, 2017a, 2017b, 2018) we have analysed bi-modal data derived from a first-year introductory course mathematics and statistics, offered in blended mode, in which several survey instruments were applied, that cover learning dispositions thought to be important in self-regulated learning. Students' preferences for alternative feedback modes, distinguishing between learners who prefer worked-out examples, tutored problem-solving or untutored problem-solving and investigating the role of learning dispositions as an antecedent of these preferences, was one of the aims of these studies. In our current paper, we continue this line of research, whereby we now focus on learning regulation and especially the timing of learning as part of a self-regulated learning process, and investigate the role of antecedents in this regulation, thereby focussing on antecedents that are part of the framework of embodied motivation (Spector and Park, 2018).

Self-regulated learning and the timing of learning

There is an abundance of empirical research investigating learning time in self-regulated learning processes. Examples of such studies can be found in the domain of classical educational studies, such as Wolters *et al*. (2017) who find that students' self-perceptions of time management are associated with self-perceived motivational and strategic aspects of self-regulated learning. Time management is also investigated in LA-based studies applying trace data, such as in Duffy and Azevedo (2015), who find that learning time invested in self-regulated learning depends on the feedback mode students are put in. However, studies focussing on the timing of learning, rather than the time of learning, seem to be scarce: irrespective of how much time students learn, how do they regulate the timing of learning time, and what antecedents can explain these timing decisions?

An exception to this pattern is the Nguyen *et al*. (2018) study that looks into students' timing of engagement with learning activities in an online, Open University module. The main aim of the study was to compare the learning design of an environmental management course with actual timing decisions of the students. The main conclusion was that large differences existed in the extent to which students kept track of the "official" course agenda, and that individual differences in time management went hand in hand with individual differences in course performance. The Nguyen *et al*. (2018) study was based on trace data of students' behaviour linked with learning activities designed by teachers: process data relating learning time decisions what and when to study, and product data relating course performance (i.e., passing various assessments and a final exam). In our current study, we aim to link similar behavioural data as used in that study, the timing decisions made in the learning process, with learning disposition data measured through surveys, to be able to compose alternative characterizations of students who prepare in time, and students who tend to postpone.

Candidates for learning dispositions that might play a role in the explanation of learning timing decisions in a self-regulated learning context are manifold. From a theoretical perspective: Schumacher and Ifenthaler (2018) decomposed the cyclical self-regulated learning process into three components, the cognitive, metacognitive, and motivational components, each counting several learner characteristics or dispositions. Starting from a more practical perspective, asking first-year students about their expectations with regard to the staff support in the development of academic competencies, Mah and Ifenthaler (2018) found five classes of competencies students aimed to develop with the support of staff: time management, learning skills, technology proficiency, self-monitoring, and research skills, that are easily mapped into the three components. In this study, we have opted to apply a broad range of instruments measuring learning disposition relevant to self-regulated learning, covering all three components and most of the reported competencies.

The two main research questions we adopt in this study build on the above-cited studies, whereby we specifically have identified sub-questions to unpack the complex, intertemporal decisions that students make when learning in our blended learning context:

RQ1 How can we explain timing decisions by students when and what to study in a blended mathematics and statistics course?

1.1 To what extent do learning regulation and timing matter, and how do they predict course performance?

1.2 To what extent can the four control variables (i.e., the three dummy variables sex, Dutch secondary education, advanced mathematics in secondary education, and score on a diagnostic entry test) explain variation in the amount of preparation, and the timing of preparation?

In order to be able to disentangle the effects of the cognitive, metacognitive, and motivational components, we will present the outcomes relating to five distinct and unique survey instruments that conceptualise learning dispositions as separate sub-questions. In terms of RQ 2.1, we will combine cognitive and metacognitive antecedents as developed by the Student Approaches to Learning (SAL) framework by Vermunt (1996) to unpack the impact on learning regulation. We include two aspects of SAL: cognitive processing strategies and metacognitive regulation strategies, from Vermunt's (1996) learning approaches instrument, encompassing aspects of cognitions and behaviours. Vermunt's framework of learning approaches distinguishes four main styles or approaches: that of meaning-directed, application-directed, reproduction-directed and undirected learning. Each approach is based on student characteristics in four different domains: cognitive processing strategies (what students do), metacognitive regulation strategies (how students plan and monitor learning), learning orientations (why students learn), and learning conceptions (how students see learning). RQ2.1 focuses on the first two of these four domains of the ILS. The processing strategies scales shaping the first domain represent *Deep* approaches to *learning* as the one pole, characterized by critical processing, relating and structuring, to *Stepwise* or surface approaches to *learning* as the opposite pole, characterized by memorizing and analysing. A third strategy is that *Concrete* or strategic *learning*: making new knowledge concrete, applying it. The metacognitive regulation strategies that constitute the second domain describe how students regulate their learning processes. Students are positioned in the spectrum from self-regulation as the main mechanism, to external regulation. The scales are *Self-regulation* of learning processes and learning content, *External-regulation* of learning processes and learning results, and *Lack of regulation* (Tempelaar *et al*., 2015, 2018; Vermunt, 1996).

RQ2 What learning dispositions act as antecedents for these timing decisions, in other words students' learning regulation?

2.1 How do Student Approaches to Learning (SAL) impact learning regulation?

The second factor we consider is educational motivation, thereby following the embodied motivation approach described in Spector and Park (2018). In that approach motivation has a multidimensional character, forms an integrated framework including affective, physical and cognitive factors. This embodied motivation encompasses several motivational perspectives described in the literature. Three of these have been adopted in this study, and are elaborated in the remainder of this section: intrinsic and extrinsic motivation, control-value theory, and motivation and engagement.

Afterwards, building on the well-known self-determination theory (Deci and Ryan, 2000), we explore the role of academic motivation on learning regulation in RQ 2.2. Academic motivations refer to the first and second so-called mini-theories of self-determination theory: the cognitive evaluation theory, concerning intrinsic motivation, and the organismic integration theory, concerning various forms of extrinsic motivation (Deci and Ryan, 2000; Sergis *et al*., 2018). The second mini-theory implies that different forms of extrinsic motivation together shape a continuum with pure intrinsic and pure extrinsic motivation as the poles, describing different degrees of internalizing extrinsic motivation into mixed states of more or less learner autonomy. The instrument Academic Motivation Scale (AMS; Vallerand *et al*., 1992), based upon Deci and Ryan's (2000) model of intrinsic and extrinsic motivation, consists of items to which students respond to the question stem "Why are you going to college?" There are seven subscales on the AMS, of which three belong to intrinsic motivation scale (intrinsic motivation to know, to accomplish, and to experience stimulating sensations), and three constitute a motivational continuum reflecting the degree of self-determined to externally controlled behaviour (identified, introjected, and external regulation). The last scale, a-motivation, constitutes a position away from the continuum: the absence of regulation, either externally directed or internally. In line with most empirical research, and to prevent collinearity, the seven scales are aggregated into *Autonomous* motivation (the sum of the three intrinsic motivation scales and identified regulation), *Controlled* motivation (the sum of introjected and external regulation), and *A-motivation*.

2.2 How does academic motivation based upon self-determination impact learning regulation?

Afterwards, we will explore the impact of the motivation and engagement wheel of Martin (2007) on learning regulation in RQ2.3. Martin (2007) breaks down learning cognitions and learning behaviours into four categories of adaptive versus maladaptive types and cognitive versus behavioural types. The classification is based on the theory that thoughts and behaviours can both enable learning, act as boosters, as well as hinder learning: act as mufflers and guzzlers. The instrument Motivation and Engagement Wheel (Martin, 2007) provides an operationalization of the four higher-order factors into eleven lower order factors. *Self-belief*, *Value of school*, and *Learning focus* shape the adaptive, cognitive factors, or cognitive boosters. *Planning*, *Task management*, and *Persistence* shape the behavioural boosters. Mufflers, the maladaptive, cognitive factors are *Anxietymotiv*, *Failure avoidance*, and *Uncertain Control*, while *Self-sabotage* and *Disengagement* are the maladaptive, behavioural factors or guzzlers. To this framework, we have added *Academic buoyancy* from a later publication (Martin and Marsh, 2008). See Tempelaar *et al*. (2015, 2018) for further elaboration.

2.3 How does the motivation and engagement framework of learning cognitions and behaviour impact learning regulation?

The third conceptualisation of educational motivation taken from Spector and Park's (2018) embodied motivation framework is adopted in RQ2.4. The Control-Value Theory of Achievement Emotions (CVTAE, Pekrun, 2006) postulates that emotions that arise in learning activities differ in valence, focus, and activation. Emotional valence can be positive (enjoyment) or negative (anxiety, hopelessness, boredom). CVTAE describes the emotions experienced about an achievement activity (e.g. boredom experienced while preparing homework) or outcome (e.g. anxiety towards performing at an exam). The activation component describes emotions as activating (i.e. anxiety leading to action) versus deactivating (i.e. hopelessness leading to disengagement). From the Achievement Emotions Questionnaire (AEQ, Pekrun *et al*., 2011) measuring learning emotions we selected four scales: positive activating emotion *Enjoyment*, negative activating emotion *Anxiety*, neutral deactivating *Boredom* and negative deactivating *Hopelessness*. Next, *Academic Control* is included as the antecedent of all learning emotions. Learning emotions of epistemic type are related to cognitive aspects of the task itself (Pekrun, 2012). Prototypical epistemic emotions are curiosity and confusion. In this RQ2.3, epistemic emotions were measured with the Epistemic Emotion Scales (EES, Pekrun and Meier, 2011), including *Surprise*, *Curiosity*, *Confusion*, *Anxiety*, *Frustration*, *Enjoyment*, and *Boredom*. See Tempelaar *et al*. (2015, 2018) for further elaboration.

2.4 How do learning emotions impact learning regulation?

Finally, we explored the potential role of four economic behavioural attitudes on learning regulation in RQ 2.5. These attitudes, part of 'other aspects of a person' in the Spector and Park (2018) framework of embodied motivation, were measured in the context of a microeconomics experiment in the same sample, but appeared being of relevance to our educational research too. These attitudes are *RiskTaking*, the tendency to risk seek rather than risk avoid; *PostPoneActivities*, the tendency to postpone activities; *TimePrefMoney*, the willingness to postpone a financial reward for a higher one in the future; and *GiveUp*, the willingness to give up today to benefit in the future.

2.5 How do attitudes in economic behaviour impact learning regulation

Methods

Context of the empirical studies

This study takes place in a large-scale introductory mathematics and statistics course for first-year undergraduate students in a business and economics programme in the Netherlands. The educational system is best described as 'blended' or 'hybrid'. The main component is face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor (see Williams *et al*., 2016 for further information on PBL and the course design). Participation in tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO (https://sowiso.nl/) and MyStatLab (MSL) (Tempelaar *et al*., 2015, 2017b). This design is based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student. Since most of the learning takes place during self-study outside class through the e-tutorials or other learning materials, class time is used to discuss solving advanced problems. Thus, the instructional format is best characterized as a flipped-classroom design (Isaías *et al*., 2017; Sergis *et al*., 2018; Williams *et al*., 2016). Using and achieving good scores in the e-tutorial practice modes is incentivized by providing bonus points for good performance in quizzes that are taken every two weeks and consist of items that are drawn from the same item pools applied in the practising mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials.

The subject of this study is the full 2017/2018 cohort of students (1027 students who enrolled the MSL tutorial). A large diversity of the student population was present: only 20.5% were educated in the Dutch high school system. Regarding nationality, the largest group, 33.5% of the students, was from Germany, followed by 24.9% Dutch and 19.5% Belgian students. In total, 55 nationalities were present. A large share of students was of European nationality, with only 4.7% of students from outside Europe. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. For example, the Dutch high school system has a strong focus on the topic of statistics but is mostly missing in high school programs of other countries. Therefore, it is crucial that this present introductory module is flexible and allows for individual learning paths (Williams *et al*., 2016). In this course, students spend on average 23.3 hours in MSL, which is nearly 30% of the available time of 80 hours for learning on the topic.

On the basis of this design, this study distinguishes three learning phases. The first learning phase prepares for the tutorial session. It is not formally assessed, other than that such preparation allows students to actively participate the discussion of the problem tasks in the tutorial session. The next phase is the preparation of the quiz session, one or two weeks later, and the third phase consists of the preparation of the final exam, at the end of the course. These later two do include formal assessments. Students' timing decisions therefore relate to the amount of preparation in each of the three consecutive phases.

Instruments and procedure

The empirical analyses described in this contribution focus on the use of the MSL e-tutorial for learning statistics. Although Pearson MyLabs can be used as a learning environment in the broad sense of the word (it contains, among others, a digital version of the textbook), they represent primarily an environment for test-directed learning and practising. Each step in the learning process is initiated by a question, and students are encouraged to (try to) answer each question. If a student does not master a question, she/he can either ask for help to solve the problem step-by-step (Help Me Solve This), or ask for a worked example (View an Example), as demonstrated in Figure 1 (left panel), in any lesson.

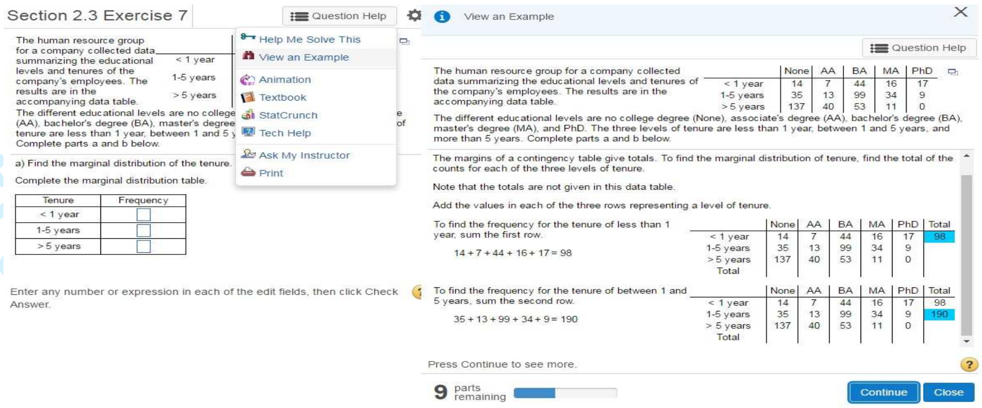

Figure 1: MSL exercise window, left panel, and worked example window, right panel

Students can call for multiple examples that differ in the context of the application of the same statistical principle, as indicated by the theory of example-based learning (Figure 1, right panel). When after studying these examples the student feels ready to make an own attempt, a new version of the problem loads (parameter based) to allow the student to demonstrate his/her newly acquired mastery.

Our study combines trace data of the MSL e-tutorial with self-report survey data measuring learning dispositions. Trace data is both of product and process type (Azevedo *et al.*, 2013). MSL reporting options for trace data are very broad, requiring making selections from the data. First, all dynamic trace data were aggregated over time, to arrive at static, full course period accounts of trace data. Second, from the large array of trace variables, a selection was made by focusing on process variables most strongly connected to timing decisions students take. In total, we selected five trace variables:

- *FinalMastery*: mastery at the end of the course, at the moment students write the exam: the proportion of the in total 160 exercises successfully answered;
- *TutorialPrep*: mastery in the first learning phase, measured at the start of the weekly tutorial sessions;
- *QuizPrep*: mastery in the second learning phase, measured at the start of the biweekly quiz sessions;
- *Tutorial%*: percentage of FinalMastery achieved in the first learning phase, as preparation of the tutorial session; and
- *Quiz%*: percentage of FinalMastery achieved in the first and second learning phase, as preparation of the quiz session.

Since tutorial sessions and quiz sessions take place at different times, we proxy the learning taking place in phases one and two by including all learning till the start of the last session, making use of the pattern that most students prepare immediately before sessions taking place, but not immediately after their sessions. *FinalMastery* (exam preparation, learning in all three phases together) is strongly collinear with *QuizPrep* and slightly less collinear with *TutorialPrep*. That collinearity is the result of the cumulative nature of these three mastery scores: quiz preparation equals tutorial session preparation plus additional preparation in between tutorial session and quiz, and exam preparation equals quiz preparation plus additional preparation after the quiz session. To diminish collinearity, and to disentangle the effects of learning intensity from the effect of learning timing, we re-expressed the two variables *TutorialPrep* and *QuizPrep* as percentages of final mastery, rather than as absolute mastery levels. That way, *Tutorial%* is the percentage of the final mastery achieved in the first phase, measured at the start of the tutorial session, and *Quiz%* is the percentage of the final mastery achieved in the first and second phase, measured at the start of the quiz session. Table I provides descriptive statistics of trace variables.

Table 1. Descriptive statistics of the trace variables

Trace variables	Mean	St.Dev.	Skewness
TutorialPrep	21.8%	25.6%	1.21
QuizPrep	52.3%	28.4%	-0.23
FinalMastery	57.7%	28.2%	-0.50
Tutorial%	30.1%	30.9%	0.93

Quiz%	90.8%	20.4%	-1.62

As can be seen from Table 1, students focus their preparations more on the quiz session than the tutorial session: the largest jump in mastery is in between these two sessions. But there exist strong individual differences in timing: some students are fully prepared for the tutorial sessions, others not at all. These individual differences result in skewness in all of the variables: negative skewness in case of quiz or exam preparation (because of a ceiling effect), positive skewness in case of tutorial preparation (floor effect). Logarithmic transforms do improve skewness scores. However, regression models as estimated in the several partial studies appear practically invariant for these transforms, and therefore, we retain the untransformed variables, for ease of interpretation of the regression outcomes.

The statistical method applied in each of the separate studies is that of hierarchical regression analysis, with the aim to discover how well timing related trace data predict course performance, and how well learning dispositions predict timing related trace data. As explained above, we restrict to linear regression models. For all models, we report standardized regression coefficients (beta), significance levels (sign.), and explained variation as R and R^2. All regression models contain three control variables that aim to account for differences between students at the start of the course:

- *Sex*: dummy variable indicating female students (43% of the students), with male students as the base value.
- *DutchEduc*: dummy variable indicating students with a Dutch high school diploma: 20%. In the mathematics program of the Dutch high school system, there is a strong emphasis on statistics. This dummy is different from the nationality dummy since quite some Dutch students have a prior education of international type.
- *MathAdv*: dummy variable indicating students who learned mathematics at an advanced level in high school (preparing for sciences and technical studies): 33% of students. All other students enjoyed mathematics at the intermediate level (preparing for social sciences) since students with only mathematics at the basic level are not admissible.
- *StatsEntry*: score on a diagnostic entry exam taken at the start of the course.

The measurement of learning dispositions as applied in the several studies takes place at the start of the course. The exceptions are both types of learning emotions that are measured about halfway through the course, to be sure that students have a proper conception of the topics and type of tasks they are asked about.

RQ 1.1: learning regulation and performance

Do timing decisions matter? In RQ1.1, we will investigate the relationship between students' learning regulation and course performance, to find out if the timing of learning, and the amount of preparation for tutorial and quiz sessions, have any impact on how well students perform in the course.

Course performance data are based on the final written exam, as well as the three biweekly, intermediate quizzes. Quiz scores are averaged, and for the exam as well as quizzes we focus on the statistics topic scores: *StatsExam* and *StatsQuiz*. Table II describes the regression models for these two performance components.

Table II. Regression models explaining course performance

	StatsExam		*StatsQuiz*	
	beta	sign.	beta	sign.
Sex	-0.024	0.415	-0.009	0.708
DutchEduc	0.097	0.001	0.107	0.000
MathAdv	0.098	0.001	0.073	0.001
StatsEntry %	0.221	0.000	0.161	0.000
FinalMastery	0.363	0.000	0.674	0.000
Tutorial%	0.120	0.001	0.005	0.857
Quiz%	0.146	0.000	0.252	0.000
	R=.561	R^2=.315	R=.762	R^2=.581

Three out of four of the control variables have a significant effect: coming from Dutch prior education, being taught mathematics at the highest level, and having high statistics proficiency as measured with the entry test. There is no gender effect. The strongest predictor of performance is, however, the final mastery level in the tool. In itself, it explains 45% of the variation in the quiz scores and 15% of the variation in exam scores. Whereby timing, represented by *Tutorial%* and *Quiz%* appears to be important too: the earlier, the better. This is because the effects are cumulative: mastery matters, the part of mastery learned before the quiz matters with an extra multiplier, and the part mastered before the tutorial session with again an extra multiplier. Differences exist between the two types of performance: for the quiz scores, there is no significant multiplier for the learning taking part in the first phase, the preparation for the tutorial session. Thus timing is relevant only to the extent mastery is achieved before the quiz takes place, but for exam scores, students benefit both from learning in the second phase, preparing the quiz session, as well as learning in the first phase, preparation of the tutorial session.

RQ 1.2: controls and learning regulation

To what extent can the four control variables that describe individual differences at the start of the course, explain variation in the amount of preparation, and the timing of preparation? Table III describes the three regression equations with control variables as the sole predictors.

Table III. Regression models explaining learning regulation from controls

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.116	0.001	0.123	0.000	0.095	0.006
DutchEduc	-0.136	0.000	-0.153	0.000	0.078	0.025
MathAdv	0.099	0.003	0.015	0.665	0.079	0.021
StatsEntry %	0.146	0.000	0.034	0.330	-0.002	0.965
	R=.230	R^2=.053	R=.196	R^2=.038	R=.143	R^2=.020

The role of the control variables in explaining learning regulation differs from their role in course performance. Female students practice more and do better time-wise: all positive and significant beta's. Students with a Dutch prior education having the better prior knowledge, practice less, certainly in the first learning phase, and somewhat compensate that in the second learning phase. Students who took advanced mathematics, and students with higher levels of prior proficiency, do reach higher mastery levels and do so in a timelier manner.

RQ 2.1: Learning approaches and learning regulation

Table IV provides the estimates of the regression model containing cognitive and metacognitive factors of Student Approaches to Learning.

Table IV. Regression models explaining learning regulation from learning strategies

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.076	0.029	0.110	0.002	0.100	0.006
DutchEduc	-0.152	0.000	-0.162	0.000	0.073	0.038
MathAdv	0.095	0.004	0.014	0.669	0.072	0.037
StatsEntry %	0.140	0.000	0.036	0.308	-0.007	0.835
Deep Learning	0.023	0.612	0.049	0.289	0.085	0.066
Stepwise Learning	0.065	0.133	0.028	0.527	-0.051	0.256
Concrete Learning	-0.155	0.000	-0.071	0.097	-0.043	0.315
Self-regulation	-0.012	0.799	-0.100	0.033	-0.063	0.185
External-regulation	0.067	0.079	0.102	0.009	0.073	0.064
Lack of regulation	-0.081	0.017	-0.037	0.280	-0.040	0.255
	R=.310	R^2=.096	R=.247	R^2=.061	R=.181	R^2=.033

The effects of learning approaches, beyond the controls, appear to be quite modest. Regarding mastery level achieved: concrete or strategic learners focus less on the digital learning environments than deep and surface learners, as do students who lack learning regulation. Regarding the timing of the preparation: there is only an impact on the amount learned in the first phase, preparation for the tutorial sessions, where externally regulated students tend to be more timely, and self-regulated students tend to be less so.

RQ2.2: Self-determination based academic motivation and learning regulation
Table V describes the regression model of the self-determination constructs.

Table V. Regression models explaining learning regulation from academic motivation

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.115	0.001	0.111	0.001	0.083	0.018
DutchEduc	-0.140	0.000	-0.151	0.000	0.080	0.024
MathAdv	0.101	0.002	0.014	0.677	0.074	0.031
StatsEntry %	0.134	0.000	0.028	0.425	-0.011	0.753
Autonomous	0.038	0.320	0.041	0.301	-0.013	0.742
Controlled	-0.057	0.128	-0.023	0.546	0.010	0.802
A-motivation	-0.133	0.000	-0.074	0.033	-0.025	0.479
	R=.283	R^2=.080	R=.216	R^2=.047	R=.139	R^2=.011

Although *Autonomous* motivation is significantly positively related to both FinalMastery and Tutorial%, these correlations do not show up in the regression models as significant betas: the effects are absorbed in the controls. Remains only a negative effect of *A-motivation* on total mastery, and on the share of mastery achieved in the first learning phase, implying that a-motivated learners both practice less and later.

RQ2.3: motivation and engagement wheel and learning regulation
The regression outcomes for the motivation and engagement wheel by Martin (2007) are illustrated in Table VI.

Table VI. Regression models explaining learning regulation from academic motivation

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.064	0.073	0.075	0.041	0.050	0.190
DutchEduc	-0.135	0.000	-0.163	0.000	0.074	0.040
MathAdv	0.095	0.003	0.010	0.756	0.062	0.074
StatsEntry%	0.109	0.001	0.028	0.574	-0.006	0.865
Self-belief	0.021	0.320	0.019	0.331	0.024	0.610
Value of school	-0.178	0.000	-0.073	0.113	0.012	0.803
Learning focus	-0.026	0.587	-0.014	0.784	0.011	0.835
Planning	0.041	0.293	0.088	0.032	0.072	0.088
Task management	0.077	0.063	0.062	0.150	-0.001	0.990
Persistence	0.056	0.165	-0.052	0.219	0.014	0.749
Academic buoyancy	-0.123	0.004	-0.107	0.017	-0.120	0.009
Anxietymotiv	-0.066	0.162	-0.086	0.079	-0.074	0.145
Failure avoidance	-0.062	0.097	-0.012	0.759	0.007	0.851
Uncertain Control	0.001	0.972	0.016	0.706	-0.027	0.534
Self-sabotage	-0.121	0.003	-0.190	0.000	-0.147	0.001
Disengagement	-0.183	0.000	-0.049	0.286	0.090	0.057
	R=.408	R^2=.167	R=.336	R^2=.113	R=.233	R^2=.054

This table includes two remarkable effects: those of *Value of school* and *Academic buoyancy*. Both of the variables are of the adaptive type, but bring negative betas into the model: *Value of school* only about total amount of preparation, *Academic buoyancy* about both amount and timing of preparation. Negative effects on both amount and timing of preparation of the maladaptive behaviours *Self-sabotage* and *Disengagement* are fully in line with theoretical expectations, as is the positive effect of adaptive behaviour *Planning* on the timing of learning.

RQ2.4: learning emotions and learning regulation

Table VII describes the regression model of the Academic Emotions Questionnaire of Pekrun *et al*. (2011) built with the epistemic emotions.

Table VII. Regression models explaining learning regulation from epistemic emotions

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.127	0.000	0.122	0.001	0.090	0.012
DutchEduc	-0.151	0.000	-0.159	0.000	0.091	0.012
MathAdv	0.084	0.015	0.010	0.785	0.078	0.028
StatsEntry %	0.141	0.000	0.035	0.319	0.006	0.861
Surprise	0.072	0.070	0.071	0.062	-0.021	0.608
Curiosity	0.007	0.873	-0.010	0.821	0.063	0.177
Confusion	-0.021	0.686	-0.066	0.206	-0.018	0.738
Anxiety	-0.141	0.004	-0.099	0.048	0.055	0.276
Frustration	0.105	0.051	0.144	0.009	-0.025	0.652
Enjoyment	-0.007	0.890	-0.027	0.599	0.002	0.969
Boredom	-0.108	0.010	-0.110	0.009	0.015	0.732
	R=.281	R^2=.079	R=.239	R^2=.057	R=.160	R^2=.026

Two epistemic have an impact on the amount and timing of learning: *Anxiety* and *Boredom*. Different from what the CVTAE predicts, both appear to be of deactivating type, where anxiety is hypothesized being of activating type. When we focus on achievement emotions, which relate to the emotions triggered by doing the learning tasks, this pattern does change: see Table IIX.

Table IIX. Regression models explaining learning regulation from academic motivation

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.099	0.004	0.110	0.002	0.094	0.009
DutchEduc	-0.136	0.000	-0.154	0.000	0.089	0.012
MathAdv	0.072	0.033	-0.002	0.949	0.066	0.061
StatsEntry %	0.137	0.000	0.033	0.357	-0.001	0.967
Academic Control	-0.009	0.841	-0.021	0.670	0.028	0.570
LAnxiety	-0.059	0.315	-0.121	0.044	0.033	0.588
LHopelessness	-0.043	0.554	0.048	0.518	-0.080	0.292
LEnjoyment	-0.046	0.261	-0.025	0.549	-0.047	0.274
LBoredom	-0.201	0.000	-0.123	0.005	-0.080	0.070
	R=.327	R^2=.107	R=.244	R^2=.060	R=.185	R^2=.034

LBoredom is still acting as a deactivating emotion, both regarding mastery and timing, but L*Anxiety* now predicts timing only, not final mastery.

RQ2.5: attitudes in economic behaviour and learning regulation

In this last RQ, we include four facets of economic behaviour as predictors of learning regulation. Table IX provides the regression model built on these attitudinal variables.

Table IX. Regression models explaining learning regulation from academic motivation

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.067	0.051	0.052	0.114	0.066	0.065
DutchEduc	-0.113	0.001	-0.123	0.000	0.068	0.056
MathAdv	0.079	0.016	-0.004	0.911	0.062	0.072
StatsEntry %	0.134	0.000	0.038	0.257	0.005	0.895

RiskTaking	-0.052	0.125	-0.057	0.079	-0.025	0.476
PostPoneActivities	-0.270	0.000	-0.363	0.000	-0.119	0.001
TimePrefMoney	0.110	0.001	0.124	0.000	0.122	0.000
GiveUp	0.041	0.213	0.022	0.492	-0.046	0.186
	R=.373	R^2=.139	R=.434	R^2=.189	R=.225	R^2=.050

Students' tendencies to postpone activities, measured in a very generic way, does clearly include learning activities: it is a strong predictor of late preparation. And with postponement comes cancellation: *PostPoneActivities* predicts final mastery level too, with a negative beta. Next, time preference, although measured in a financial context, impacts learning too. Students who are restraint, willing to wait for their reward, appear to learn more timely and learn more.

Discussion and conclusions

Although there is a wide body of literature on multi-modal analytics, few studies have linked various conceptualisations of self-regulation (e.g., learning approaches, motivation, emotions) with how students are making decisions when and what to study in a large scale blended mathematics and statistics module. In an attempt to decompose the amount of preparation and timing of preparation as good as possible, we reformulated our target variables as final mastery, and percentages of final mastery reached in the first learning phase, preparing the tutorial session, and in the second learning phase, preparing the quiz session. In terms of our first main research question, we collected evidence that these variables do matter in describing the learning process: they explained 32% and 58% of variation in the two performance variables. The explanation of final mastery and timing variables themselves appeared more difficult. Especially the two timing variables appeared to depend on other variables beyond the set of learning dispositions investigated in this study.

Final mastery is explained by about 5% by controls. Learning dispositions add to that, where up to 17% explained variation when variables from the motivation and engagement wheel are applied. Timing decisions were more difficult to predict. That was already visible from the role of the control variables: they only explained 4% and 2% of the variation in the two timing variables. While our previous research (Nguyen *et al.*, 2016; Tempelaar *et al.*, 2015, 2017 a, b, 2018) found that learning dispositions significantly predicted aggregate learning processes and outcomes, in this study with more fine-grained temporal data learning dispositions seemed to add to that but generally were not able to create the same amount of predictive power as in the mastery case. The single exception to this pattern was the case of explaining in-time preparation for the tutorial sessions: the model of the last RQ2.5 with only two attitudinal variables as predictors, tendency to postpone activities and time preference, which explained 19% of the variation of students' preparations in the first learning phase.

The context of this paper is a course offered in blended learning format, where students apply different modes of learning. It is from that digital mode we learn so many details by analysing trace data, but the learning in the other mode, the face-to-face mode based on problem-based learning, stays largely unmeasured. These one-sided measurements obviously impact the models we find in several of the individual studies. Several explanatory variables that on theoretical grounds were expected to describe adaptive facets of learning behaviour appeared in the regression models with negative betas, and vice versa, some variables describing maladaptive facets of learning, turned up with positive betas. This could potentially be explained by the blended nature, with the problem-based learning mode being the most demanding learning mode, and the digital mode offering more learning scaffolds to students. "Stronger" students might have had less need for these scaffolds, in contrast to the weaker students, explaining these patterns in the use of the MSL. A good example of this phenomenon is provided by RQ2.1, investigating the role of learning approaches. Self-regulation of learning predicted out-of-time preparation, whereas external regulation of learning predicted in-time preparation, without significant effects on the amount of preparation. This can only be understood as self-regulated learners deciding themselves on the timing of the learning, where externally regulated learners stuck to the scheme provided in the course manual. Another example was offered in RQ2.3, where we found that *Value of school* and *Academic buoyancy* carried negative betas, both about mastery and timing, although both of these dispositions were expected to be of the adaptive type. Apparently, these students might have focussed on learning in the face-to-face mode, less accessible for many other students who lacked these adaptive dispositions, and were this way less dependent on learning in the digital mode.

Behavioural, maladaptive dispositions have a less complex role to play. In this study there were several of them, in most of the instruments: the *Lack of regulation* metacognitive strategy, the *A-motivation* scale from self-determinism, the guzzlers *Self-sabotage* and *Disengagement* from the motivation and engagement wheel and the *PostPoneActivities* variable demonstrated negative betas for both mastery and timing. These dispositions seemed to negatively impact the learning on a generic level, rather than influence any individual mode of learning only. In the context of the framework of embodied motivation (Spector and Park, 2018), main conclusion of this study is that the role played by the several motivation perspectives demonstrates wide variation. For instance, learning regulation suggests to be invariant over different constellations of intrinsic and extrinsic motivation, with only a-motivation having some impact. Other perspectives, such as the control-value framework or motivation and engagement wheel, however do have stronger impacts. Overall, this study showed that learners with different self-regulation strategies opted for a range of complex, intertemporal and blended learning decisions.

Future research should explore whether or not students' self-regulations over time were influenced by these learning decisions, and how we as educators can provide appropriate support for students who might lack sufficient self-control.

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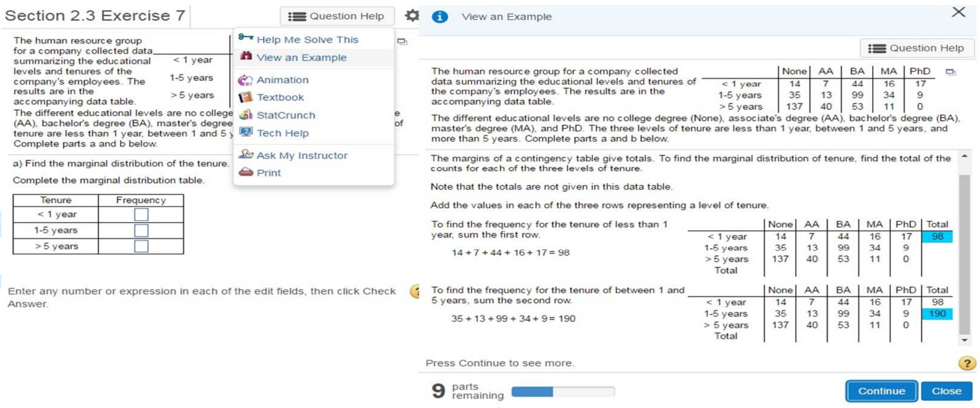
Section 2.3 Exercise 7
Question Help
The human resource group for a company collected data summarizing the educational levels and tenures of the company's employees. The results are in the accompanying data table.
< 1 year
1-5 years
> 5 years
The different educational levels are no college
(AA), bachelor's degree (BA), master's degree
tenure are less than 1 year, between 1 and 5 y
Complete parts a and b below.
Help Me Solve This
View an Example
Animation
Textbook
StatCrunch
Tech Help
Ask My Instructor
Print
a) Find the marginal distribution of the tenure.
Complete the marginal distribution table.
Tenure
Frequency
< 1 year
1-5 years
> 5 years
Enter any number or expression in each of the edit fields, then click Check Answer.
View an Example
Question Help
The human resource group for a company collected data summarizing the educational levels and tenures of the company's employees. The results are in the accompanying data table.
None AA BA MA PhD
< 1 year 14 7 44 16 17
1-5 years 35 13 99 34 9
> 5 years 137 40 53 11 0
The different educational levels are no college degree (None), associate's degree (AA), bachelor's degree (BA), master's degree (MA), and PhD. The three levels of tenure are less than 1 year, between 1 and 5 years, and more than 5 years. Complete parts a and b below.
The margins of a contingency table give totals. To find the marginal distribution of tenure, find the total of the counts for each of the three levels of tenure.
Note that the totals are not given in this data table.
Add the values in each of the three rows representing a level of tenure.
To find the frequency for the tenure of less than 1 year, sum the first row.
14 + 7 + 44 + 16 + 17 = 98
None AA BA MA PhD Total
< 1 year 14 7 44 16 17 98
1-5 years 35 13 99 34 9
> 5 years 137 40 53 11 0
Total
To find the frequency for the tenure of between 1 and 5 years, sum the second row.
35 + 13 + 99 + 34 + 9 = 190
None AA BA MA PhD Total
< 1 year 14 7 44 16 17 98
1-5 years 35 13 99 34 9 190
> 5 years 137 40 53 11 0
Total
Press Continue to see more.
9 parts remaining
Continue
Close

Trace variables	Mean	St.Dev.	Skewness
TutorialPrep	21.8%	25.6%	1.21
QuizPrep	52.3%	28.4%	-0.23
FinalMastery	57.7%	28.2%	-0.50
Tutorial%	30.1%	30.9%	0.93
Quiz%	90.8%	20.4%	-1.62

	StatsExam		*StatsQuiz*	
	beta	sign.	beta	sign.
Sex	-0.024	0.415	-0.009	0.708
DutchEduc	0.097	0.001	0.107	0.000
MathAdv	0.098	0.001	0.073	0.001
StatsEntry %	0.221	0.000	0.161	0.000
FinalMastery	0.363	0.000	0.674	0.000
Tutorial%	0.120	0.001	0.005	0.857
Quiz%	0.146	0.000	0.252	0.000
	$R=.561$	$R^2=.315$	$R=.762$	$R^2=.581$

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.116	0.001	0.123	0.000	0.095	0.006
DutchEduc	-0.136	0.000	-0.153	0.000	0.078	0.025
MathAdv	0.099	0.003	0.015	0.665	0.079	0.021
StatsEntry %	0.146	0.000	0.034	0.330	-0.002	0.965
	R=.230	R^2=.053	R=.196	R^2=.038	R=.143	R^2=.020

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.076	0.029	0.110	0.002	0.100	0.006
DutchEduc	-0.152	0.000	-0.162	0.000	0.073	0.038
MathAdv	0.095	0.004	0.014	0.669	0.072	0.037
StatsEntry %	0.140	0.000	0.036	0.308	-0.007	0.835
Deep Learning	0.023	0.612	0.049	0.289	0.085	0.066
Stepwise Learning	0.065	0.133	0.028	0.527	-0.051	0.256
Concrete Learning	-0.155	0.000	-0.071	0.097	-0.043	0.315
Self-regulation	-0.012	0.799	-0.100	0.033	-0.063	0.185
External-regulation	0.067	0.079	0.102	0.009	0.073	0.064
Lack of regulation	-0.081	0.017	-0.037	0.280	-0.040	0.255
	R=.310	R^2=.096	R=.247	R^2=.061	R=.181	R^2=.033

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.115	0.001	0.111	0.001	0.083	0.018
DutchEduc	-0.140	0.000	-0.151	0.000	0.080	0.024
MathAdv	0.101	0.002	0.014	0.677	0.074	0.031
StatsEntry %	0.134	0.000	0.028	0.425	-0.011	0.753
Autonomous	0.038	0.320	0.041	0.301	-0.013	0.742
Controlled	-0.057	0.128	-0.023	0.546	0.010	0.802
A-motivation	-0.133	0.000	-0.074	0.033	-0.025	0.479
	R=.283	R^2=.080	R=.216	R^2=.047	R=.139	R^2=.011

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.064	0.073	0.075	0.041	0.050	0.190
DutchEduc	-0.135	0.000	-0.163	0.000	0.074	0.040
MathAdv	0.095	0.003	0.010	0.756	0.062	0.074
StatsEntry%	0.109	0.001	0.028	0.574	-0.006	0.865
Self-belief	0.021	0.320	0.019	0.331	0.024	0.610
Value of school	-0.178	0.000	-0.073	0.113	0.012	0.803
Learning focus	-0.026	0.587	-0.014	0.784	0.011	0.835
Planning	0.041	0.293	0.088	0.032	0.072	0.088
Task management	0.077	0.063	0.062	0.150	-0.001	0.990
Persistence	0.056	0.165	-0.052	0.219	0.014	0.749
Academic buoyancy	-0.123	0.004	-0.107	0.017	-0.120	0.009
Anxietymotiv	-0.066	0.162	-0.086	0.079	-0.074	0.145
Failure avoidance	-0.062	0.097	-0.012	0.759	0.007	0.851
Uncertain Control	0.001	0.972	0.016	0.706	-0.027	0.534
Self-sabotage	-0.121	0.003	-0.190	0.000	-0.147	0.001
Disengagement	-0.183	0.000	-0.049	0.286	0.090	0.057
	R=.408	R^2=.167	R=.336	R^2=.113	R=.233	R^2=.054

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.127	0.000	0.122	0.001	0.090	0.012
DutchEduc	-0.151	0.000	-0.159	0.000	0.091	0.012
MathAdv	0.084	0.015	0.010	0.785	0.078	0.028
StatsEntry %	0.141	0.000	0.035	0.319	0.006	0.861
Surprise	0.072	0.070	0.071	0.062	-0.021	0.608
Curiosity	0.007	0.873	-0.010	0.821	0.063	0.177
Confusion	-0.021	0.686	-0.066	0.206	-0.018	0.738
Anxiety	-0.141	0.004	-0.099	0.048	0.055	0.276
Frustration	0.105	0.051	0.144	0.009	-0.025	0.652
Enjoyment	-0.007	0.890	-0.027	0.599	0.002	0.969
Boredom	-0.108	0.010	-0.110	0.009	0.015	0.732
	R=.281	R^2=.079	R=.239	R^2=.057	R=.160	R^2=.026

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.099	0.004	0.110	0.002	0.094	0.009
DutchEduc	-0.136	0.000	-0.154	0.000	0.089	0.012
MathAdv	0.072	0.033	-0.002	0.949	0.066	0.061
StatsEntry %	0.137	0.000	0.033	0.357	-0.001	0.967
Academic Control	-0.009	0.841	-0.021	0.670	0.028	0.570
LAnxiety	-0.059	0.315	-0.121	0.044	0.033	0.588
LHopelessness	-0.043	0.554	0.048	0.518	-0.080	0.292
LEnjoyment	-0.046	0.261	-0.025	0.549	-0.047	0.274
LBoredom	-0.201	0.000	-0.123	0.005	-0.080	0.070
	R=.327	R^2=.107	R=.244	R^2=.060	R=.185	R^2=.034

	FinalMastery		*Tutorial%*		*Quiz%*	
	beta	sign.	beta	sign.	beta	sign.
Sex	0.067	0.051	0.052	0.114	0.066	0.065
DutchEduc	-0.113	0.001	-0.123	0.000	0.068	0.056
MathAdv	0.079	0.016	-0.004	0.911	0.062	0.072
StatsEntry %	0.134	0.000	0.038	0.257	0.005	0.895
RiskTaking	-0.052	0.125	-0.057	0.079	-0.025	0.476
PostPoneActivities	-0.270	0.000	-0.363	0.000	-0.119	0.001
TimePrefMoney	0.110	0.001	0.124	0.000	0.122	0.000
GiveUp	0.041	0.213	0.022	0.492	-0.046	0.186
	R=.373	R^2=.139	R=.434	R^2=.189	R=.225	R^2=.050